The Puzzle of Non-Participation in Continuing Training – An Empirical Study of Chronic vs. Temporary Non-Participation*

Uschi Backes-Gellner, Johannes Mure and Simone N. Tuor

Although participation in continuing vocational training is often found to be associated with considerable individual benefits, a puzzlingly large number of people still do not take part in training. In order to solve the puzzle we distinguish between temporary and chronic non-participants. Previous studies have shown that training participants and non-participants differ in unobservable characteristics and therefore self-select into training or not. We show that even non-participants cannot be treated as a homogeneous group: there are those who never take part in training (chronic non-participants) and those who are not currently taking part (temporary (non-)participants). Using a unique data set of non-participants commissioned by the German "Expert Commission on Financing Lifelong Learning" and covering a very large number of individuals not taking part in training, we separate and compare chronic and temporary non-participants. By estimating a sample selection model using maximum likelihood estimation we take potential selection effects into account: temporary (non-)participants may be more motivated or may have different inherent skills than chronic non-participants. We find that chronic non-participants would have higher costs than temporary (non-)participants and their short-term benefits associated with their current jobs would be lower. However, in the long run even chronic non-participants would benefit similarly from participation due to improved prospects on the labor market. The results indicate that chronic non-participants either misperceive future developments or suffer from an exceptionally high discount rate, which in turn leads in their view to a negative cost-benefit ratio for training.

* This paper was released for publication in May 2007.

Contents

1 Introduction

Lifelong learning and continuing vocational training are becoming more and more important – a trend driven primarily by demographics and rapid technological change. On the one hand, the decline in birth rates and an aging workforce may cause a shortage of skilled labor, strengthening the importance of continuing vocational training (Bellmann 2003). On the other hand, technological change is strongly skill-biased, shifting labor demand toward more educated workers.[1] Employees with low levels of education run the risk of earning lower wages or, even worse, of being crowded out of the labor market because many jobs are disappearing (Spitz-Oener 2006). All this should cause a strong incentive to participate in continuing vocational training. Moreover, a large number of studies have shown that participation in continuing vocational training boosts individual wages.[2] Recent research has also found non-monetary benefits, such as a reduced risk of becoming unemployed.[3] However, many individuals still refrain from participating in continuing vocational training. Even individuals who leave school with few or no qualifications, and whose only way to catch up would be to participate in continuing training, often decide not to participate in any continuing training measure (Schröder/Schiel/Aust 2004). Furthermore, Groot/Maassen van den Brink (2003) point to the existence of different training tracks, where workers not participating in further training in one year are likely to belong to the group of non-participants in the next year as well.

The question we raise in our paper is how the puzzle can be solved, i. e. why is it that we find high returns to training for all participants on the one hand, and a large number of people not participating in training on the other hand. We argue that the solution is to be found in unobservable characteristics of two different groups of non-participants, namely temporary and chronic non-participants. This distinction has not been used before and the results are promising.

There is vast empirical literature devoted to estimating the (positive) impact of training, e. g. on the participants' wages, but only a few empirical papers analyze the rate of return that non-participants would have if they had taken part in continuing vocational training. Vignoles/Galindo-Rueda/Feinstein (2004) analyze the effect of work-related training on wage growth, but focus only on middle-aged male workers. They estimate a selection model – taking into account that the training decision could be endogenous – and find substantial selection effects. Those workers who have received training measures gain substantial wage benefits, whereas non-participating workers would not have gained higher wages if they had participated. Groot (1995) analyzes the impact of an investment in firm-related training on wages and he finds that participants do have a positive rate of return. But the wage gain a non-participant would have received if he had participated is negative. Moreover, Leuven/Oosterbeek (2002) show that the return to work-related training is overestimated when self-selection is not taken into account. There is also similar evidence in the field of initial vocational training. Wolter/Mühlemann/Schweri (2006) find that most of the apprenticeships in Switzerland generate net benefits for the participating firms. But they also show that if non-participating firms were to start training apprentices, they would incur significantly higher net costs compared to the participating firms, which follows from the fact that non-participants face much more unfavorable cost-benefit ratios. Thus, all these results indicate that due to the absence of sufficient benefits or due to higher costs, not participating in training could be a rational decision. But the question still remains as to the characteristics of those individuals for whom it may not pay to take part in training. It can be assumed that especially the distinction between different qualification levels is fundamental. Highly skilled workers seem to capture a larger share of the productivity effects of continuing training than low-skilled workers (Kuckulenz 2006), influencing the cost-benefit ratio of participation in further training.

Bassanini et al. (2005) studied the determinants driving the probability of receiving training and found that educational attainment and the skill-intensity of the occupation exert a positive impact. There seem to be complementarities between higher levels of education on the one hand and continuing training on the other. So individuals who are already disadvantaged in schooling and vocational education are more likely not to participate in lifelong learning later in life. Jenkins et al. (2003) found that the more qualified individuals are, the more likely they are to return to learning later in life. Moreover, the training probability decreases with age, and both part-time and temporary workers are less often found in the group of participants (Bassanini et al. 2005). In sum, training participants and non-participants differ in observable as well as in unobservable characteristics.

[1] Chennells/Van Reenen (1999) survey the evidence on the correlation between technology and skills and come to the conclusion that the technological change is skill-biased.
[2] See Frazis/Loewenstein (2005) for US; Bassanini et al. (2005) and Pfeiffer (2000) for Europe.
[3] Büchel/Pannenberg (2004).

In addition, we argue in this paper that non-participants cannot and also should not be treated as a homogeneous group. We distinguish between chronic and temporary non-participants for the first time and study their (potential) returns to continuing training separately. We are fortunate in being able to use a unique data set of non-participants with more than 1200 individuals.[4] This survey allows the distinction between individuals never taking part in training (chronic non-participants) and individuals currently not taking part, i. e. in the year of the survey (temporary non-participants). According to the character of the data set our paper aims to study the differences between the two groups of non-participants and particularly to find out why some people never take part in continuing training. The structure of the paper is as follows: the next section covers the theoretical framework, a simple cost-benefit model which mainly serves the purpose of structuring our empirical analysis and indicating important explanatory variables. Section 3 explains the econometric models and the estimation methods applied. The data set used is described in section 4. The results of the estimation of costs and benefits are presented in section 5, and conclusions are drawn in the last section.

2 Theoretical framework: the investment decision

To structure our empirical analysis of individual decisions to participate in training, we use standard human capital theory as a framework.[5] We assume that an individual's participation decision has to be seen as an investment decision. Individuals bear costs of participating in continuing training and in later periods expect various kinds of benefits in return. If discounted individual returns exceed individual costs, it pays to invest; otherwise it is rational not to invest in training (see e. g. Borjas 2005: 240 ff. or Lazear 1998: 136 ff.).[6] Or to be more precise, an individual only invests in continuing vocational training if the present value of his or her individual benefits exceeds the present value of his or her individual costs, i. e. if

$$\sum_{t=1}^{T} \frac{B_{ijt}}{(1+r)^t} > \sum_{t=1}^{t+z} \frac{C_{ijt}}{(1+r)^t} \tag{1}$$

If inequation (1) does not hold, it would not be rational for individuals to invest in training. According to this model we expect chronic non-participants either to have higher costs and/or to have lower returns associated with participating in training than temporary non-participants. Higher costs could be due to lower ability, bad learning experience, or emotional distress triggered by schooling situations. Lower returns could be due to systematic differences in their workplaces, in motivation, in effort or career prospects.

The total costs (C) of an employee[7] (i) participating in training measure (j) in period (t) can be separated into direct costs and indirect or opportunity costs. Direct costs include participation fees, expenses for books, transportation costs or expenses for childcare, as well as non-monetary costs such as disliking learning or negative feelings attached to training due to bad past learning experience. Opportunity costs include either the forgone salary an individual could have earned if he had not taken part in continuing training (in the case of unpaid leave) or the loss of leisure. Some direct cost components (e. g. participation fees) may be the same for both chronic non-participants and temporary non-participants. Other cost components – especially non-monetary direct costs (such as learning stress) – may be substantially higher for chronic non-participants. Opportunity costs could also differ substantially but the overall effect is unclear ex ante. Compared to chronic non-participants, temporary non-participants may be individuals with higher ability or motivation, they may learn more quickly and finish the same training measure in a shorter time. However, their forgone income per time unit may also be higher. At the same time, for individuals with lower income it might be more difficult to compensate for forgone earnings, so even lower absolute amounts of forgone income would still prevent them from participating, so the direction of the overall effect is theoretically not clear but remains an empirical question.

The benefits (B) also have two components: directly measurable benefits such as an increase in pay, and indirect benefits such as an increase in job security or long-term labor market prospects.

Furthermore, since the decision depends on the present value of costs and benefits, the remaining

[4] We thank the Expert Commission on Financing Lifelong Learning for collecting the data and for allowing us to use it.
[5] Becker (1975).
[6] Although in many cases the company may also bear some or even most of the costs of a training measure and therefore gets some of the returns, we only concentrate on the part of the costs that the individual bears and the parts of the returns that the individual receives. So if the company and the individual split costs and benefits, we would just have the individual's part in our empirical analysis.

[7] Full-time employees, part-time employees, unemployed persons, training participants as well as unemployed persons who would like to start working (again) in the next two years belong to this group.

time in the labor market (T) and the individual discount rate play a crucial role. Individuals with a high discount rate r are more present-oriented. As a consequence they are less likely to accept costs today to gain benefits at some time in the future. This could for example be the case for chronic non-participants and would thus explain their non-participation. Taken together, the decision never to take part can occur either because chronic non-participants cannot afford the associated costs (monetary and/or non-monetary), because of low short-term benefits associated with training participation, or because of a high discount rate or a low remaining time in the labor market.[8] Since our cost and return data use only qualitative variables and are not in currency units (such as €) we cannot compute quantitative cost-benefit ratios. Therefore, we have to study costs and benefits separately in the following.

3 Estimation model and methods

In this section we present the estimation model for the costs that result from taking part in continuing vocational training as well as for various benefits that result from participation. In all our estimations we control for potential selection effects.

3.1 Costs

The basic equation we estimate can be written as:

$$\begin{aligned} \text{Costs} = \beta_0 + \beta_1 \cdot \text{VocTraining} + \beta_2 \cdot \text{ProfStatus} + \\ \beta_3 \cdot \text{EmpCharacteristics} + \\ \beta_4 \cdot \text{IndCharacteristics} + \delta \cdot X + u \end{aligned} \tag{2}$$

Since the dependent variable *costs* cannot be measured directly because our sample consists of non-participants only, we argue that we can use the individual's *WILLINGNESS TO PAY* as a proxy providing us with a good lower bound for training costs. Since our non-participants all decided not to take part in training it seems reasonable to assume that the actual training costs were higher than their individual willingness to pay which is why they decided not to take part. Accordingly, *WILLINGNESS TO PAY* provides us with the lower bound of actual training costs and can in this sense be used as a proxy for training costs.[9]

The independent variable "VocTraining" includes various dummy variables for vocational training measures, such as *APPRENTICESHIP*, *FULL-TIME VOCATIONAL SCHOOL*, *MASTER CRAFTSMAN* and *UNIVERSITY*. Professional status, represented by "ProfStatus", includes variables indicating different categories such as *BLUE-COLLAR WORKER*, *WHITE-COLLAR WORKER* and *SELF-EMPLOYED* person.[10] "EmpCharacteristics" consists of variables describing the employment situation or workplace of the individual, including for example *NUMBER OF EMPLOYEES* in the company or dummies such as *FULL-TIME EMPLOYEE*, *USE A COMPUTER AT WORK OR AT HOME* or *KNOWLEDGE AND SKILL NEEDS CHANGE FREQUENTLY*. Furthermore, we use individual control variables ("IndCharacteristics") such as *NET INCOME*, *AGE*, *GENDER* and having CHILDREN (*KIDS*) and we control for industry-specific effects by adding INDUSTRY dummies ("X"). In a second step, we add the *MARITAL STATUS* and *INTERACTION TERMS* between the individual characteristics *GENDER* and *KIDS* as well as between *MARRIED* and *KIDS*. Findings from the German Socio-economic Panel (see Bellmann 2003) show that married women who live in a household with children are less likely to take part in continuing training whereas men in the same situation are more likely to participate. In a third step, we include a variable representing an individual's *TIME PREFERENCE* and estimate the basic and the extended equation again. Controlling for present- or future-orientedness, it is possible to consider the impact of costs on the participation decision exclusively. For a full list of the variables included in the estimation models and the respective descriptive statistics see Table 1 (in the appendix).

A major methodological problem is that the variable *costs* can only be observed for people who have at some time taken part in continuing vocational training. In our sample these are the temporary non-participants, who by definition must have taken part in training at some time in the past but not in the survey year (strictly speaking they are not only temporary non-participants but also temporary participants, which is what we make use of to estimate our cost variable). So for temporary (non-)participants we have (past) training costs, but for chronic non-participants such data obviously cannot be available. So we have a sample selection problem or an incidental truncation problem as it is called by Wooldridge (2003: 587–591). Whether we observe the (de-

[8] Another potential reason causing a similar result could be that chronic non-participants lack necessary long-term information and thus cannot anticipate future benefits or possible job-offers correctly.

[9] Individuals had to specify the amounts they were willing to spend on continuing training out of five categories (in € p.a.). We use the upper limit per category as a proxy for the lower bound of actual training costs. See also section 4.

[10] We do not include civil servants because they are in a different situation as regards wages and job security. One could also consider excluding self-employed persons. But, as the results remain stable with or without this category, we decided not to do so in order to analyze a larger sample of non-participants.

pendent) variable depends on the participation decision and it is therefore known for temporary (non-) participants only. It can be assumed that individuals are not randomly selected into the two groups[11], i. e. temporary (non-)participants presumably have systematically different costs than chronic non-participants (for example due to ability differences). Thus, an OLS regression of equation (2) produces inconsistent and biased estimates of the coefficients. The approach we use to solve this problem is as follows:[12]

First we model the probability of a person being a participant (participation equation):

$$y^*_{2i} = z'_i\gamma + u_{2i} \quad \text{(latent variable } y^*_{2i}) \tag{3}$$

where $u_{2i} \sim N(0, 1)$,; we observe $y_{2i} = 1$ (an individual took part in continuing vocational training) if $y^*_{2i} > 0$. In this step we use the whole data set (temporary (non-)participants as well as chronic non-participants).

In the second step we examine y_{1i} and take into account that y_{1i} is only observed if $y_{2i} = 1$ (outcome equation), meaning that in this step we can only include temporary (non-)participants:

$$y_{1i} = x'_1\beta + u_{1i} \tag{4}$$

where $u_{1i} \sim N(0, \sigma_1^2)$ and y_{1i} is the costs associated with participation in continuing training. The error terms u_{1i} and u_{2i} are bivariate normal with correlation ϱ. In our specification we follow Wooldridge (2003: 589), who strongly recommends that x is a strict subset of z and that there is at least one element of z that is not also in x (Wooldridge 2003: 589). Therefore, any explanatory variable in the regression equation should also be an explanatory variable in the selection equation. Moreover, we need at least one variable that affects selection but does not have a partial effect on y. The expected value of y_{1i} can then be written as:

$$E(y_{1i}|z'_i, y_{2i} = 1) = x'_i\beta + \varrho\lambda(z'_i\gamma) \tag{5}$$

where $\lambda(z'_i\gamma)$ is the inverse Mills ratio (Wooldridge 2003: 588). If there is no correlation between the two equations ($\varrho = 0$), then the participation and outcome equations are independent and the OLS estimates of β would be unbiased. But if there is a correlation between the participation decision and the cost determinants, then there is an omitted variable problem, $\lambda(z'_i\gamma)$. That is why we first test whether there is a selection bias. If the null hypothesis ($\varrho = 0$) cannot be rejected, there is no selection problem and OLS estimations would be appropriate, otherwise selection effects have to be taken into account and the model explained above has to be used. To estimate such a model we can either choose the two-step estimation method recommended by Heckman (1976) or the maximum likelihood estimation recommended by Wooldridge (2003: 591). The latter is used in this study, as it is asymptotically unbiased, asymptotically normal and more efficient than the two-step estimator, provided that the appropriate assumptions are met (cf. Wooldridge 2003: 591, or Breen 1996: 40).[13]

3.2 Benefits

The following equation is used to assess the benefits associated with taking part in continuing training:

$$P(\text{Benefit} = 1|x) = \Phi(\beta_0 + \beta_1 \cdot \text{VocTraining} + \beta_2 \cdot \text{ProfStatus} + \beta_3 \cdot \text{EmpCharacteristics} + \beta_4 \cdot \text{IndCharacteristics} + \delta \cdot X + u) \tag{6}$$

where *benefit* is a binary response variable. Due to data restrictions and in contrast to the cost analysis, we have to estimate the direct and indirect benefits of training in separate steps. First we use *INCREASE IN PAY* as a dependent variable, indicating a direct benefit. To examine indirect benefits, we use *IMPROVING JOB SECURITY* as well as *IMPROVING EMPLOYMENT OUTLOOK* as dependent variables. The independent variables are the same as in the cost equation and, as in the cost estimations, we have to solve the problem of unobserved heterogeneity. Individuals who have taken part in continuing vocational training may also be more motivated or may have different inherent skills and may therefore have higher earnings or better job prospects. Thus, the effect of participation would be overestimated. It is therefore important to use a maximum-likelihood probit estimation with selection instead of a simple probit estimation. The estimation procedure follows the same approach as that used in the case of incidental truncation with a metric dependent variable in chapter 3.1. The major difference is that there is a binary dependent variable. Therefore the outcome equation is as follows:

$$y^*_{1i} = x'_i\beta + u_{1i} \tag{7}$$

where $u_{1i} \sim N(0, 1)$ and $y_{1i} = 1$ if $y^*_{1i} > 0$.

[11] Leuven/Oosterbeek (2002).

[12] As the data set used does not have a panel structure, fixed effects estimation (Wooldridge, 2003: 461–467; Wooldridge 2002: 265–279), which would also be a possible approach to take potential selection effects into account, cannot be used.

[13] There are other studies preferring the two-step estimator, but there seems to be no common strategy (see Puhani (1997) for a survey of criticism of the different methods).

4 Data and descriptive statistics

Our empirical estimation is based on a unique data set commissioned by the German "Expert Commission on Financing Lifelong Learning". It covers individuals who did not participate in continuing training in the period from September 2001 to August 2002.[14] The data set contains information from computer-assisted telephone interviews with 1264 employees between 19 and 64 years of age and living in Germany. The sample is a representative sample of non-participants which resulted as a by-product of a survey of participants commissioned by the German Federal Institute for Vocational Education and Training (Bundesinstitut für Berufsbildung (BIBB)) for a separate project (cf. Beicht/Krekel/Walden 2006). Unfortunately, the participants' data were not available for this study, therefore our analysis is restricted to the non-participants sample as described in Schröder/Schiel/Aust (2004). Since our main interest lies in differences between chronic and temporary non-participants in training, we separate the respondents into those who have never participated in training[15] – referred to as chronic non-participants – and those who have taken part in continuing vocational training at least once in the past, but not during the survey period – referred to as temporary (non-)participants.[16]

Continuing training is defined very broadly in this study. It is any kind of further learning, be it formal, non-formal and/or informal learning or of a general or vocational nature, after the completion of initial vocational training (Timmermann et al. 2002: 55). Thus our training measure includes formal training programs that may take place in a company or at a continuing vocational training institute, it also includes informal on-the-job training (such as e.g. quality circles or job rotation) and even self-directed learning or conference participation.

The *training* variable is a dummy variable taking the value 1 if someone belongs to the temporary (non-) participants and 0 if someone is a chronic non-participant.[17] About one third of the people interviewed (419) belong to the latter category of chronic non-participants.

Regarding our dependent variables, people were asked about the costs and benefits associated with participation in continuing vocational training. (A full list of all variables and their overall means and means broken down into temporary and chronic non-participants is given in Table 1.) Descriptive statistics indicate that chronic non-participants rate the benefits associated with participation in continuing vocational training considerably lower than temporary (non-)participants. On average, chronic non-participants have a lower *willingness to pay* than temporary (non-)participants: the former are willing to invest about € 300, the latter more than € 500 on average, which we use as our proxy for training costs (because only the people in the latter group really know what they are talking about). The validity of the cost proxy that we obtain by this estimation is backed up by empirical results from the survey of participants given in Beicht/Krekel/Walden (2006). Based on data from actual participants they find that participants spend an average of € 502 on their training, which is astonishingly close to our proxy, i.e. the amount that temporary (non-)participants are willing to pay for continuing vocational training, which is € 520. With regard to our explanatory variables, we find that chronic non-participants are characterized by rather low or even no qualifications. For example, 20 % of chronic non-participants but only 5 % of temporary (non-)participants have no secondary school certificate. As a proxy for the discount rate we use the strength of an individual's preference for enjoying life and having enough time for personal interests and leisure. Descriptive statistics show that chronic non-participants are far more present-oriented than temporary (non-)participants, which indicates that present-orientedness could indeed have an influence on the individual training decision.

As explained in section 3, it is important to take selection effects into account. The equation determining the participation decision should contain a selection variable that satisfies two conditions. On the one hand the selection variable has to correlate

[14] For details of the survey see Schröder/Schiel/Aust (2004).

[15] We are aware that the period since entering the labor market and in which there is an opportunity of taking part in continuing vocational training is shorter for younger employees. But on the other hand, there is the inverse impact on the training probability of young and older workers caused by differences in the remaining time in the labour market. However, as we control for age, the estimated differences in costs and benefits should not be biased.

[16] Thus, we deliberately do not differentiate between the various further vocational training measures which the data set contains. Moreover, the duration of continuing vocational training might have an impact on returns (Budria/Pereira 2004). As we do not have duration data, we cannot make these differences. But for our main objective, analyzing why some people never take part in continuing vocational training, this is not crucial.

[17] If people had not participated during the period from September 2001 to August 2002, they were asked about participation in the past. Various types of training were specified and people had to answer for each type of training separately if they had taken part before the survey period. Thus, the risk of not remembering a participation and consequently being assigned to the chronic non-participants should be very small.

with the participation decision. On the other hand it should not have an effect on the outcome of interest (the cost or benefit variables). Closely related to other empirical findings for Germany which use the number of children to identify the decision to take part in training because children put higher strains on the time budget (Büchel/Pannenberg 2004), we use the variable "taking part causes too much stress due to my job and private obligations" for the selection equation. Slightly less than half of the chronic non-participants (46 %), but only a third of the temporary (non-)participants (35 %) state that this was decisive for their non-participation, so the variable is correlated with the participation decision. In contrast, it is obvious that the stress a person expects due to job or family obligations is not related to the outcome variables such as direct training costs or marginal benefits resulting from a training measure. If we look at our estimation results, both assumptions are confirmed: the identification variable has a highly significant impact on the probability of being a temporary (non-)participant (cf. section 5.3), but this is neither the case for costs nor for benefits.

After eliminating observations with missing data, a sample of 527 individuals is left for analysis.[18] Of these, 163 observations are censored and are therefore not included when estimating the outcome equation separately.[19]

5 Econometric results

5.1 Costs

Table 2 in the appendix (model 1)[20] presents the results of estimating the basic equation. The selection model, using a maximum likelihood estimator, supports the view that there is selection into training based on unobservable characteristics: the hypothesis that there is no sample selection ($\varrho = 0$) is rejected at the 5 % level. Thus, sample selection is a problem and the costs of training vary based on observable as well as unobservable characteristics. As can be seen, the selection effect is negative ($\varrho = -0.1219$) which means that temporary (non-)participants have lower costs *ceteris paribus* than chronic non-participants, which is a highly plausible result. The unobserved characteristics that increase the likelihood of ever taking part in continuing vocational training are associated with lower actual expenditures.

Turning to the predicted costs[21], the result shown above is confirmed: on average chronic non-participants pay slightly more than temporary (non-)participants. The former have a predicted amount of about € 504, which is substantially higher than what the chronic non-participants are willing to pay (cf. section 4). A very important determinant seems to be vocational training: employees with an apprenticeship or a university degree or equivalent have significantly lower costs associated with training participation than employees without a secondary school certificate. Income does not have a significant impact on willingness to pay, so forgone salary does not seem to be crucial in the training decision. Therefore, the loss of leisure and the direct costs must be the major driving force. Individuals with the lowest level of schooling (no secondary school certificate) can be assumed to have the greatest difficulty in learning at school and might therefore also have a lower ability and less motivation to keep on learning later in their life because they would need much more time and effort than individuals with a higher qualification level. In addition, they are assumed to be much more averse to learning. Including a variable representing time preferences (model 2) does not yield a substantial change. The result shown above also holds for the models with additional individual characteristics and interaction terms (models 3 and 4). None of the added variables has an impact on the costs associated with continuing participation in training.

To summarize, individual training costs seem to play a major role in the individual participation decisions: the costs that chronic non-participants would have to bear are significantly higher than those actually borne by temporary (non-)participants.

[18] The non-participants survey contains 1264 observations. As already explained, we do not include civil servants. Moreover, information about costs and benefits associated with training participation is not known for each non-participant. Finally, only interviewed persons for whom the vocational training, as well as specific individual and employment characteristics, are known can be included in the empirical analysis.

[19] Employees who did not choose one of the vocational training categories were generally excluded because they form a very small and heterogeneous group. Just a few people are family workers, employees subject to social insurance contributions or people who have not yet worked. They cannot be included because most of them have missing values in the other variables and with just one or two observations left, it is not possible to provide evidence.

[20] The tables only provide limited information about the selection equations. Full tables are available form the authors upon request.

[21] Predicted costs and benefits are estimated as follows: given the estimated coefficients of the outcome equation obtained by only including temporary non-participants but taking into account potential selection effects, we can plug in every non-participant in the regression. Thus, we obtain predicted costs as well as benefits for each of them.

5.2 Benefits

In our first estimation we use *increase in pay* as a dependent variable (Table 3 in the appendix). Estimating the basic equation, the hypothesis that the outcome and participation equation can be estimated separately cannot be rejected ($\varrho = 0$). Therefore, we can use a simple probit model to estimate the outcome equation. The results are given in Table 3, models 1–2. We find that the significant variables generally take their expected signs: white-collar workers are more likely to have received an increase in pay than blue-collar workers, which is highly relevant since the latter are more likely to belong to the group of chronic non-participants. This is also true for employees holding a job characterized by frequent changes in knowledge and skill needs. Moreover, having children is associated with a lower likelihood of a wage increase. Calculating the marginal effects at the means of the independent variables shows that being a white-collar worker (compared to a blue-collar worker) is associated with a 9.1 percentage point higher likelihood of a pay increase, and the need for a frequent change of knowledge and skills with a 12.8 percentage point higher likelihood, while having children is associated with an 8.5 percentage point lower likelihood of an increase in pay. Moreover, having a master craftsman's diploma enters with a significant negative coefficient. They are less likely (9.1 percentage points) to have received a wage increase than someone without a secondary school leaving certificate. The results remain stable when the time preference variable is added (Table 3, models 3–4). Including the variables representing marital status (*married and single mother/father*) as well as interaction terms between *gender* and *children* and between *marriage* and *children* yields almost the same results with the exception of the variable *kids*, which no longer has a significant impact (Table 3, last four models).

To summarize, the predicted probability of having received an increase in pay is about 15 percent: temporary (non-)participants have on average a higher and chronic non-participants a lower likelihood of receiving a pay rise. On the whole, the results are in line with those of Vignoles/Galindo-Rueda/Feinstein (2004), who find that only those workers who actually participate in continuing training are able to realize wage gains. For those workers who did not participate in training, participation would not have been associated with a short-term wage gain in their current job.

Secondly, we consider the benefit of training in terms of job prospects. We first look at differences in *job security*. Again, we assume that individuals who occasionally take part in continuing training differ from those who never take part in training, which is supported by the results of the basic equation estimation. There is a positive selection effect of $\varrho = 0.8448$. The hypothesis that there is no sample selection ($\varrho = 0$) is rejected at the 5 % level (Table 4 in the appendix, models 1 and 2). Temporary (non-) participants are less likely to lose their jobs as a result of their inherent ability or other unobserved characteristics and not necessarily because of their participation in continuing vocational training. With respect to job security, being male, using a computer at work and working in a large company are associated with a lower likelihood of becoming unemployed. In calculating the marginal effects at the means of the independent variables we find that using a computer has a statistically and also an economically significant positive impact of 13.8 percentage points on the likelihood of increased job security. Bearing in mind that employees who use a computer at work are more likely to take part in continuing training than other workers, it can be assumed that it is particularly important for these people to keep on learning later in life in order not to lose their job. Being a male as compared to being a female increases the likelihood by 11.6 percentage points. Finally, firm size affects job security, but the effect is not practically large: if a firm grows by 1000 employees, the likelihood of participation in training increases by only 1.1 percentage points. On average the probability of increased job security is 21.4 %, whereas the predicted probability for chronic non-participants is slightly lower and the probability for temporary (non-)participants is higher. The difference between the two groups is about 4 %. Even after adding the variable representing present-orientedness, the above-mentioned results remain stable. The hypothesis that there is no sample selection can still be rejected, although only at the 10 % level (Table 4, models 3 and 4). The variable does not have a significant impact on job security, but – indirectly indicating a usually unobserved characteristic – reduces the influence of unobserved characteristics which usually make the coefficient of a separately estimated probit model biased. Nevertheless, estimating a selection model seems preferable. The last four models in Table 4 differ insofar as some variables indicating the marital status and interaction terms between *gender* and *kids* as well as between *marriage* and *kids* are added. This has an influence on the significance of some of the "Individual Characteristics" variables, which are worth looking at: the likelihood of an increase in job security falls with increasing age but at a diminishing rate. The most notable result is the significant positive coefficient of having children. The marginal effect is very high – at 36.5 percentage points (and 39.2 percentage points respectively). Turning to the added variables, we find that being married has a significant and positive impact on job security (21.8 and 22.7 percentage points respectively). But if a married couple has children, the likelihood of having a secure job is reduced by 30.9 (and 32.7) percentage points. Bearing in mind that the coefficient of the variable *kids* is also very high, families with children are still less likely to lose their jobs.

Turning to *prospects on the labor market*, we find that a separate estimation of the outcome equation does not yield biased estimates of the coefficients: the hypothesis that there is no sample selection (ϱ = 0) cannot be rejected at the 10 % level irrespective of the included explanatory variables. As the regressions of the models including marital status and the interaction terms have a higher significance, we turn to the second part of Table 5 (in the appendix). In particular, the coefficients of the variables *married* and *married with kids* are highly significant. While being married has a positive effect on the likelihood of increased prospects on the labor market, having children in addition has a significant negative impact; taking into account the coefficient of *kids*, which is positive but not significant, it is no longer clear whether there is really a difference between married couples with and without children. Interestingly, working full-time, which has neither an influence on costs nor on the likelihood of an increase in pay or job security, has a significantly positive effect. Working full-time instead of part-time (or other forms) is associated with a marginal effect of 16.9 percentage points. As with job security, firm size enters with a positive and significant coefficient with an effect that is not practically large. The predicted probability of continuing training as a necessary condition for increased prospects on the labor market is 48.5 % for temporary (non-)participants and 47.7 % for chronic non-participants. Almost half of each group benefits from participation in continuing vocational training as far as increased prospects on the labor market are concerned. Therefore, this seems to be a highly important and non-negligible factor.

To summarize, chronic non-participants would not gain as much as temporary (non-)participants in terms of increased job security. Chronic non-participants are more likely to be found in unskilled jobs. Therefore, they are most likely not faced with constantly increasing requirements at the workplace due to technological change, but with the situation that their job may disappear. Thus, considering only their current job, the decision not to take part in training seems to be a rational decision in the short and medium term because chronic non-participants would indeed not gain much in their current job – and they know it. However, since it is precisely these workers who are at a higher risk of losing their jobs[22] it would be important for them to think more in the long term. As we have seen, continuing vocational training would be necessary to improve their employment outlook. Participation in training could provide them with knowledge enabling them to do more complex or even completely different work, which in turn would make it easier to find new jobs once they lose their current jobs. Thus, information asymmetries seem to play a crucial role: chronic non-participants would benefit as much as temporary (non-)participants in terms of employment outlook, but do not seem to realize that in addition to returns associated with their current jobs (where returns are indeed very low) participation in training could also lead to better prospects on the labor market and could therefore help them to find new jobs if they are laid off.

Our hypothesis on benefits is therefore only partly confirmed. Chronic non-participants would indeed have lower benefits regarding their current jobs,[23] but they would still benefit as much as temporary (non-)participants in terms of long-term labor market prospects. Another important result is that chronic and temporary non-participants have to be distinguished in empirical studies because they are rather different in their costs and benefits. Therefore, studies that do not differentiate between chronic and temporary non-participation underestimate the returns to education for temporary (non-) participants on the one hand and on the other hand overestimate the returns to education for chronic non-participants. So if, for example, these two groups are not differentiated, results on returns to training cannot be expected to be reliable.

5.3 Participation decision

Given the above results it seems important to distinguish between chronic and temporary non-participants because they are faced with a significantly different cost-benefit structure of training. Accordingly, the question is what distinguishes the two non-participation groups. Table 6 (in the appendix) provides probit regression results concerning the probability of taking part in continuing vocational training. The first two models of the Table give results

[22] Almost one in five unskilled workers was unemployed in Germany in 2003 (iwd 2006).
[23] This result corresponds with Groot's (1995) finding that non-participants would have a negative wage gain in the case of participation.

for the basic equation (model 1) and for the basic equation with a variable representing time preference added (model 2); the last two models provide both models with some more individual characteristics. The following results are similar in all of the models. The likelihood of taking part in continuing vocational training is significantly higher for a master craftsman, a worker who has completed an apprenticeship or who holds a university degree or equivalent than for a worker without a secondary school certificate. The results are consistent with those reported in the literature: Bassanini et al. (2005), for example, find that having a lower level of education exerts a negative impact on the probability of training participation. Surprisingly, there is no significant distinction between different professional statuses. The need for changing knowledge and skills as well as the use of a computer significantly increases the likelihood of being a temporary (non-)participant rather than a chronic non-participant. As expected, the likelihood of being a chronic non-participant is significantly higher for employees who consider training to be too much stress in addition to their jobs and private obligations. The regressions with the variable representing time preferences indicate that orientation towards the present (high discount rate) is negatively associated with the likelihood of being a participant. Individuals with a high discount rate obviously invest only if they can expect an immediate gain. Entering variables indicating marital status and interaction terms between different individual characteristics leads to the following: contrary to the results usually found in the literature (see e.g. Bassanini et al. 2005), people who are employed full-time are significantly less likely to belong to the group of temporary (non-) participants. Single mothers/fathers as well as people who are married (no matter whether they have children or not) are more likely to take part in continuing vocational training. There is no significant difference between mothers and fathers.

6 Conclusions

Although continuing training is becoming increasingly important, a large proportion of the workforce surprisingly does not participate in training. This seems particularly puzzling since a large number of studies demonstrate that participation in training leads to substantial positive returns. In our paper we show that non-participants are not a homogeneous group and that the distinction between chronic non-participants and temporary (non-)participants is fundamental to solving the puzzle. We compare chronic non-participants with temporary (non-)participants (employees who have taken part in continuing training at least once in the past but are not currently participating). We assume that the two groups differ in observable as well as unobservable characteristics and use selection models in our empirical analysis in order to account for this problem. We study differences in the costs, benefits and/or discount rates of the two groups of non-participants. We find that individuals who are chronic non-participants would have to bear higher costs if they were to participate. Moreover, the benefits associated with their current job would be lower, i. e. any pay increases or reduction in unemployment risk would be smaller for chronic non-participants than for temporary (non-)participants. However, the results indicate that in the long run chronic non-participants would benefit from participation in terms of improved prospects on the labor market, which indicates that the discount rate of chronic non-participants is probably exceptionally high. Although participation in training would not protect those people from losing their jobs, it would increase their likelihood of finding new jobs once they have become unemployed, but this may seem to be too far in the future to be important at the present time. Angrist/ Lavy (2004) argue similarly with respect to investments in schooling by low-achieving students and suggest using short-term financial rewards to reduce the problem of exceptionally high discount rates. Based on a randomized trial, they present evidence that financial incentives do indeed increase high school certification rates.

Another potential reason could be that chronic non-participants lack the necessary information and can therefore not anticipate future benefits or possible job-offers correctly. Thus, when thinking about policy implications it seems necessary to increase workers' awareness of returns that are not directly associated with their current job, but which might lie far in the future and which might therefore often be neglected. Small financial incentives attached to completing training measures could be an option with which to overcome the problem of exceptionally high discount rates.

References

Angrist, Joshua D./Lavy, Victor (2004): The Effect of High Stakes High School Achievement Awards: Evidence from a Group Randomized Trial. IZA Discussion Paper Number 1146, IZA, Bonn.

Bassanini, Andrea/Booth, Alison/Brunello, Giorgio/De Paola, Maria/Leuven, Edwin (2005): Workplace Training in Europe. IZA Discussion Paper Number 1640, IZA, Bonn.

Becker, Gary S. (1975): Human Capital. A Theoretical and Empirical Analysis with Special Reference to Education. New York/London: Columbia University Press.

Beicht, Ursula/Krekel, Elisabeth M./Walden, Günther (2006): Berufliche Weiterbildung – Welche Kosten und welchen Nutzen haben die Teilnehmenden? Bonn: Federal Institute for Vocational Training BIBB.

Bellmann, Lutz (2003): Datenlage und Interpretation der Weiterbildung in Deutschland. Schriftenreihe der Expertenkommission Finanzierung Lebenslangen Lernens, Vol. 2, Bielefeld.

Borjas, George J. (2005): Labor Economics. Third Edition. New York: McGraw-Hill/Irwin.

Breen, Richard (1996): Regression Models: Censored, Sample-Selected, or Truncated Data. In: Quantitative Applications in the Social Sciences, Vol. 07, Number 111. London: Sage University Papers.

Büchel, Felix/Pannenberg, Markus (2004): Berufliche Weiterbildung in West- und Ostdeutschland – Teilnehmer, Struktur und individueller Ertrag. In: Zeitschrift für ArbeitsmarktForschung, Vol. 37, Number 2, pp. 73–126.

Budria, Santiago/Pereira, Pedro T. (2004): On the Returns to Training in Portugal. IZA Discussion Paper Number 1429, IZA, Bonn.

Chennells, Lucy/Van Reenen, John (1999): Has Technology Hurt Less Skilled Workers? Institute for Fiscal Studies, Working Paper Series Number W99/27, London.

Frazis, Harley/Loewenstein, Mark A. (2005): Reexamining the Returns to Training: Functional Form, Magnitude, and Interpretation. In: Journal of Human Resources, Vol. 40, Number 2, pp. 453–674.

Groot, Wim (1995): The Wage Effects of Investments in Enterprise-Related Training. In: Empirical Economics, Vol. 20, Number 1, pp. 133–147.

Groot, Wim/Maasen van den Brink, Henriette (2003): Firm-related training tracks: a random effects ordered probit model. In: Economics of Education Review, Vol. 22, Number 6, pp. 581–589.

Heckman, James J. (1976): The Common Structure of Statistical Models of Truncation, Sample Selection, and Limited Dependent Variables and a Simple Estimator for Such Models. In: Annals of Economic and Social Measurement, Vol. 5, pp. 475–492.

Institut der deutschen Wirtschaft (2006): Geringqualifizierte. Anderswo häufiger in Lohn und Brot. In: Informationsdienst des Instituts der deutschen Wirtschaft iwd, Number 15, April 2006.

Jenkins, Andrew/Vignoles, Anna/Wolf, Alison/Galindo-Rueda, Fernando. (2003): The determinants and labour market effects of lifelong learning. In: Applied Economics, Vol. 35, Number 16, pp. 1711–1721.

Kuckulenz, Anja (2006): Wage and Productivity Effect of Continuing Training in Germany: A Sectoral Analysis. Centre for European Economic Research (ZEW), Discussion Paper Number 06–025, Mannheim.

Lazear, E. P. (1998): Personnel Economics for Managers. New York: John Wiley&Sons.

Leuven, Edwin/Oosterbeek, Hessel (2002): A New Approach to Estimate the Wage Returns to Work-Related Training. IZA Discussion Paper Number 526, IZA, Bonn.

Pfeiffer, Friedhelm (2000): Training and Individual Performance in Europe: Evidence from Microeconometric Studies. Centre for European Economic Research (ZEW), Discussion Paper Number 00–28, Mannheim.

Puhani, Patrick A. (1997): Foul or Fair? The Heckman Correction for Sample Selection and Its Critique. A Short Survey. Centre for European Economic Research (ZEW), Discussion Paper Number 97–07, Mannheim.

Schröder, Helmut/Schiel, Stefan/Aust, Folkert (2004): Nichtteilnahme an beruflicher Weiterbildung, Motive, Beweggründe, Hindernisse. Schriftenreihe der Expertenkommission Finanzierung Lebenslangen Lernens, Vol. 5, Bielefeld.

Spitz-Oener, Alexandra (2006): Technical Change, Job Tasks and Rising Educational Demands: Looking Outside the Wage Structure. In: Journal of Labor Economics, Vol. 24, Number 2, pp. 235–270.

Timmermann, Dieter/Färber, Gisela/Backes-Gellner, Uschi/Bosch, Gerhard/Nagel, Bernhard (2002): On the Way to Financing Lifelong Learning. Interim Report of the Expert Commission on Financing Lifelong Learning. Bielefeld.

Vignoles, Anna/Galindo-Rueda, Fernando/Feinstein, Leon (2004): The Labour Market Impact of Adult Education and Training: A Cohort Analysis. In: Scottish Journal of Political Economy, Vol. 51, Number 2, pp. 266–280.

Wolter, Stefan C./Mühlemann, Samuel/Schweri, Jürg (2006): Why some firms train apprentices and many others do not. In: German Economic Review, Vol. 7, Number 3, pp. 249–264.

Wooldridge, Jeffrey M. (2003): Introductory Econometrics: A Modern Approach. Mason (OH): Thomson South-Western.

Wooldridge, Jeffrey M. (2002): Econometric Analysis of Cross Section and Panel Data. Cambridge/Massachusetts: MIT Press.

Appendix

Table 1

List of variables used

Variable	Notes	Total Mean (Std. dev.)	Temporary Mean (Std. dev.)	Chronic Mean (Std. dev.)
Participation in continu-ing vocational training	Dummy = 1 if a person is a temporary (non-)participant, otherwise 0	0.6647 (0.4723)		
Willingness to pay	Willingness to pay in Euro	449.2002 (978.3869)	519.3101 (1040.6510)	309.8956 (824.8570)
Increase in pay	Dummy = 1 if a person received an increase in pay, otherwise 0	0.1593 (0.3661)	0.1618 (0.3686)	0.1538 (0.3615)
Job security	Dummy = 1 if continuing vocational training is necessary to improve job security, otherwise 0	0.3608 (0.4804)	0.3753 (0.4845)	0.3316 (0.4714)
Prospects on the labor market	Dummy = 1 if continuing vocational training is necessary to improve prospects on the labor market, otherwise 0	0.4939 (0.5002)	0.5286 (0.4995)	0.4253 (0.4950)
Independent variables				
Without secondary school certificate	Reference	0.0951 (0.2934)	0.0536 (0.2254)	0.1772 (0.3823)
Apprenticeship	Several years of vocational training in school and on the job	0.7207 (0.4488)	0.7407 (0.4385)	0.6810 (0.4667)
Full-time vocational school	Several years of vocational training in school	0.1621 (0.3687)	0.1686 (0.3746)	0.1494 (0.3569)
Master craftsman		0.0501 (0.2182)	0.0664 (0.2492)	0.0177 (0.1321)
University of applied sciences		0.0280 (0.1651)	0.0370 (0.1890)	0.0101 (0.1002)
University		0.0475 (0.2129)	0.0600 (0.2377)	0.0228 (0.1494)
Blue-collar worker	Reference	0.3744 (0.4842)	0.3193 (0.4665)	0.4835 (0.5004)
White-collar worker		0.5586 (0.4968)	0.6066 (0.4888)	0.4633 (0.4993)
Self-employed person		0.0671 (0.2502)	0.0741 (0.2621)	0.0532 (0.2246)
Full-time employee	Dummy = 1 if a person is employed full-time, otherwise 0	0.5509 (0.4976)	0.5581 (0.4969)	0.5367 (0.4993)
Change	Dummy = 1 if knowledge and skill needs change, otherwise 0	0.5035 (0.5002)	0.5352 (0.4991)	0.4400 (0.4971)
Meeting the needs	Dummy = 1 if knowledge and skills meet the needs, otherwise 0	0.8239 (0.3810)	0.8346 (0.3718)	0.8026 (0.3986)
Computer private	Dummy = 1 if a person uses a computer privately, otherwise 0	0.6916 (0.4620)	0.7663 (0.4235)	0.5431 (0.4988)
Computer at work	Dummy = 1 if a person uses a computer at work, otherwise 0	0.5899 (0.4921)	0.7048 (0.4565)	0.3631 (0.4816)
Number of employees		1744.6100 (3470.5110)	1936.5700 (3634.3540)	1342.0280 (3064.8140)
Age		40.7342 (10.1024)	41.0051 (9.7997)	40.1964 (10.6704)
Age squared		1761.2450 (840.6438)	1777.3320 (825.8251)	1729.3190 (869.4981)
Sex	Dummy = 1 if a person is male, otherwise 0	0.4440 (0.4971)	0.4674 (0.4993)	0.3975 (0.4900)
Kids	Dummy = 1 if a person has at least one child, otherwise 0	0.5686 (0.4955)	0.5755 (0.4947)	0.5552 (0.4977)
Net income	Net income in Euro	1319.3630 (1151.1690)	1412.6960 (1259.7100)	1140.6910 (882.3360)
Married	Dummy = 1 if a person is married, otherwise 0	0.6746 (0.4687)	0.6918 (0.4620)	0.6405 (0.4805)
Single mother/father	Dummy = 1 if a person is a single mother/father, otherwise 0	0.0850 (0.2789)	0.0793 (0.2704)	0.0962 (0.2952)
Present-oriented	Dummy = 1 if enjoying life and having enough time for personal interests/leisure is a very important aim in life, otherwise 0	0.3422 (0.4746)	0.3252 (0.4687)	0.3756 (0.4849)
Strain	Dummy = 1 if continuing vocational training is too much strain besides job and private obligations, otherwise 0	0.3888 (0.4877)	0.3514 (0.4777)	0.4639 (0.4993)

Table 2
Costs

	Basic equation	… & time preference	… & interaction terms	… & time preference, interaction terms
	MLE model 1	MLE model 2	MLE model 3	MLE model 4
Outcome equation: costs				
Vocational training				
Apprenticeship	–284.9283* (152.7667)	–283.9043* (153.1549)	–283.4516* (153.5701)	–282.5839* (153.9265)
Full-time vocational school	45.7697 (153.5818)	48.5427 (153.4299)	63.9263 (155.8915)	66.3883 (155.8606)
Master craftsman	184.8608 (214.6432)	196.9994 (216.5999)	174.8389 (224.8583)	186.0187 (226.3103)
University of applied sciences	–279.7773* (151.5675)	–283.0289* (150.7788)	–292.7146* (155.9092)	–297.5709* (155.7774)
University	–271.0859** (135.8782)	–260.1087* (135.1057)	–283.5607** (140.0331)	–272.3519* (139.2009)
Professional status				
White-collar worker	64.1820 (106.5599)	64.6401 (106.5510)	52.0351 (106.4128)	52.3419 (106.3334)
Self-employed person	348.3002 (258.4311)	366.4148 (259.1558)	338.2618 (261.7224)	355.9353 (262.0150)
Employment characteristics				
Full-time employee	34.3136 (105.8100)	42.8373 (109.9947)	46.0780 (118.6091)	55.3230 (122.6371)
Change	–14.8042 (87.6586)	–22.9363 (89.4323)	–8.9708 (89.1424)	–16.9396 (90.7878)
Meeting the needs	55.0591 (148.1695)	56.1919 (146.7103)	55.3781 (150.0058)	56.8354 (148.4188)
Computer private	34.7630 (92.1616)	27.2637 (93.1956)	42.5436 (94.6205)	35.2355 (95.2035)
Computer at work	129.8048 (82.4911)	133.1337 (83.7198)	126.4736 (82.1286)	129.7036 (83.4052)
Number of employees	–0.0115 (0.0100)	–0.0107 (0.0099)	–0.0106 (0.0102)	–0.0097 (0.0101)
Individual characteristics				
Age	16.8039 (25.9540)	15.5175 (25.7850)	12.7199 (25.5104)	11.3838 (25.4447)
Age squared	–0.3272 (0.3209)	–0.3125 (0.3180)	–0.2836 (0.3115)	–0.2686 (0.3096)
Sex	–117.8094 (135.9695)	–128.1258 (134.9939)	–130.4606 (154.3147)	–138.2807 (152.8725)
Kids	–110.2118 (101.0877)	–102.8876 (100.8610)	–19.4856 (153.4032)	2.7676 (156.6122)
Net income	0.0130 (0.0279)	0.0135 (0.0278)	0.0128 (0.0291)	0.0134 (0.0291)
Married			119.0190 (148.2023)	121.9026 (148.3600)
Single mother/father			–69.3903 (157.4123)	–75.6189 (159.3330)
Male & kids			5.1082 (178.9591)	–0.4381 (179.0223)
Married & kids			–98.7678 (149.4645)	–112.1637 (153.2088)
Time preference				
Present-oriented		91.4999 (95.8714)		92.5311 (95.9817)
Constant	408.5194 (495.6430)	379.9509 (500.2964)	393.0891 (468.9033)	361.4693 (472.7255)
Prob > χ^2	**0.0289**	**0.0382**	**0.0514**	**0.0676**
N	527	527	527	527
Participation equation: participation in continuing vocational training				
Influence on participation decision				
Strain	–0.4459*** (0.1276)	–0.4376*** (0.1279)	–0.4759*** (0.1296)	–0.4664*** (0.1301)
Prob > χ^2	**0.0208**	**0.0249**	**0.0268**	**0.0272**
ρ	–.1219	–.1148	–.1164	–.1102

*Robust std. errors in parentheses; *** (0.01), ** (0.05), * (0.10).*

Table 3

Increase in pay

	Basic equation			… & time preference			… & interaction terms			… & time preference, interaction terms		
	MLE model 1	Probit model 2		MLE model 3	Probit model 4		MLE model 5	Probit model 6		MLE model 7	Probit model 8	
		Coef.	ME		Coef.	ME		Coef.	ME		Coef.	ME
Outcome equation: increase in pay												
Vocational training												
Apprenticeship	–0.0052 (0.2504)	0.0366 (0.2559)	0.0086 (0.0601)	–0.0134 (0.2474)	0.0300 (0.2560)	0.0071 (0.0602)	0.0091 (0.2698)	0.0367 (0.2518)	0.0087 (0.0590)	–0.0005 (0.2642)	0.0304 (0.2519)	0.0072 (0.0591)
Full-time vocational school	0.0649 (0.3387)	0.0241 (0.3242)	0.0058 (0.0788)	0.0620 (0.3368)	0.0152 (0.3244)	0.0036 (0.0782)	0.0550 (0.3462)	0.0335 (0.3239)	0.0081 (0.0790)	0.0521 (0.3479)	0.0248 (0.3240)	0.0060 (0.0784)
Master craftsman	–0.5705 (0.3763)	–0.4757 (0.3301)	–0.0907* (0.0482)	–0.5788 (0.3565)	–0.4879 (0.3296)	–0.0923* (0.0474)	–0.5378 (0.4102)	–0.4852 (0.3303)	–0.0917* (0.0475)	–0.5522 (0.3881)	–0.4965 (0.3297)	–0.0932** (0.0467)
University of applied sciences	0.0351 (0.4285)	0.1530 (0.3812)	0.0391 (0.1040)	0.0150 (0.4224)	0.1501 (0.3815)	0.0382 (0.1037)	0.0543 (0.4915)	0.1250 (0.3856)	0.0315 (0.1025)	0.0354 (0.4896)	0.1230 (0.3866)	0.0309 (0.1025)
University	–0.2816 (0.3816)	–0.2176 (0.3767)	–0.0469 (0.0723)	–0.2962 (0.3765)	–0.2355 (0.3813)	–0.0502 (0.0717)	–0.2694 (0.4133)	–0.2258 (0.3747)	–0.0483 (0.0711)	–0.2894 (0.4034)	–0.2430 (0.3793)	–0.0515 (0.0705)
Professional status												
White-collar worker	0.3694 (0.2347)	0.3951* (0.2132)	0.0906* (0.0472)	0.3631 (0.2369)	0.3953* (0.2130)	0.0905* (0.0471)	0.3917* (0.2239)	0.3948* (0.2183)	0.0902* (0.0480)	0.3889* (0.2275)	0.3951* (0.2181)	0.0902* (0.0479)
Self-employed person	–0.0216 (0.4756)	–0.1150 (0.4377)	–0.0261 (0.0938)	–0.0340 (0.4752)	–0.1443 (0.4400)	–0.0322 (0.0915)	–0.0533 (0.5077)	–0.1040 (0.4456)	–0.0236 (0.0962)	–0.0681 (0.5146)	–0.1333 (0.4481)	–0.0298 (0.0939)
Employment characteristics												
Full-time employee	0.3105 (0.2374)	0.2791 (0.2493)	0.0625 (0.0518)	0.3036 (0.2341)	0.2681 (0.2473)	0.0601 (0.0516)	0.3590 (0.2771)	0.3324 (0.2676)	0.0732 (0.0539)	0.3529 (0.2717)	0.3209 (0.2654)	0.0708 (0.0536)
Change	0.4587 (0.3124)	0.5490*** (0.1736)	0.1278*** (0.0388)	0.4552 (0.3141)	0.5614*** (0.1732)	0.1305*** (0.0386)	0.4998* (0.2899)	0.5418*** (0.1757)	0.1258*** (0.0393)	0.4999 (0.3051)	0.5541*** (0.1755)	0.1284*** (0.0392)
Meeting the needs	0.0344 (0.2499)	0.0021 (0.2502)	0.0005 (0.0596)	0.0311 (0.2469)	–0.0021 (0.2492)	–0.0005 (0.0595)	0.0066 (0.2561)	–0.0066 (0.2527)	–0.0016 (0.0604)	0.0037 (0.2545)	–0.0110 (0.2515)	–0.0026 (0.0603)
Computer private	0.0229 (0.3882)	0.1802 (0.2098)	0.0407 (0.0448)	0.0166 (0.3665)	0.1887 (0.2100)	0.0425 (0.0446)	0.0894 (0.4103)	0.1677 (0.2121)	0.0379 (0.0455)	0.0821 (0.4005)	0.1757 (0.2123)	0.0396 (0.0452)
Computer at work	–0.0013 (0.4743)	0.1839 (0.2176)	0.0419 (0.0469)	–0.0115 (0.4350)	0.1839 (0.2175)	0.0419 (0.0468)	0.0953 (0.4832)	0.1853 (0.2177)	0.0421 (0.0467)	0.0826 (0.4582)	0.1859 (0.2176)	0.0422 (0.0466)
Number of employees	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
Individual characteristics												
Age	–0.0027 (0.0616)	0.0032 (0.0635)	0.0008 (0.0152)	–0.0010 (0.0615)	0.0058 (0.0640)	0.0014 (0.0153)	0.0098 (0.0626)	0.0102 (0.0631)	0.0024 (0.0150)	0.0125 (0.0627)	0.0131 (0.0635)	0.0031 (0.0151)
Age squared	–0.0002 (0.0007)	–0.0002 (0.0008)	0.0000 (0.0002)	–0.0002 (0.0007)	–0.0002 (0.0008)	–0.0001 (0.0002)	–0.0003 (0.0008)	–0.0003 (0.0008)	–0.0001 (0.0002)	–0.0003 (0.0008)	–0.0003 (0.0008)	–0.0001 (0.0002)
Sex	0.0502 (0.2733)	0.1183 (0.2304)	0.0282 (0.0547)	0.0538 (0.2708)	0.1320 (0.2291)	0.0314 (0.0543)	0.1178 (0.2811)	0.1416 (0.2611)	0.0336 (0.0616)	0.1252 (0.2845)	0.1551 (0.2612)	0.0367 (0.0615)
Kids	–0.3286 (0.2069)	–0.3534* (0.1898)	–0.0847* (0.0459)	–0.3340 (0.2042)	–0.3634* (0.1881)	–0.0870* (0.0456)	–0.4364 (0.5959)	–0.4599 (0.5973)	–0.1101 (0.1438)	–0.4390 (0.5991)	–0.4751 (0.5945)	–0.1136 (0.1431)
Net income	0.0000 (0.0001)	0.0001 (0.0001)	0.0000 (0.0000)	0.0000 (0.0001)	0.0001 (0.0001)	0.0000 (0.0000)	0.0001 (0.0001)	0.0001 (0.0001)	0.0000 (0.0000)	0.0001 (0.0001)	0.0001 (0.0001)	0.0000 (0.0000)
Married							–0.1688 (0.4694)	–0.1019 (0.3679)	–0.0252 (0.0942)	–0.1884 (0.4682)	–0.1083 (0.3722)	–0.0268 (0.0956)
Single mother/father							–0.2362 (0.6698)	–0.1445 (0.5408)	–0.0323 (0.1135)	–0.2575 (0.6737)	–0.1456 (0.5438)	–0.0325 (0.1138)
Male & kids							–0.1911 (0.3803)	–0.1638 (0.3561)	–0.0375 (0.0781)	–0.1976 (0.3752)	–0.1642 (0.3565)	–0.0375 (0.0780)
Married & kids							0.2503 (0.5862)	0.2399 (0.5948)	0.0578 (0.1451)	0.2519 (0.5787)	0.2463 (0.5941)	0.0593 (0.1448)
Time preference												
Present-oriented				–0.0394 (0.2026)	–0.1006 (0.1696)	–0.0236 (0.0390)				–0.0684 (0.2138)	–0.1021 (0.1698)	–0.0238 (0.0389)
Constant	–0.7730 (2.1637)	–1.5787 (1.3215)		–0.7070 (2.0278)	–1.5615 (1.3248)		–1.3224 (2.2655)	–1.7008 (1.3358)		–1.2493 (2.1782)	–1.6844 (1.3384)	
Prob > χ^2	**0.1412**	**0.0203**		**0.1829**	**0.0210**		**0.1767**	**0.0524**		**0.2257**	**0.0519**	
N	527	363		527	363		527	363		527	363	
Participation equation: participation in continuing vocational training												
Influence on part. decision												
Strain	–0.4109*** (0.1563)			–0.4004** (0.1553)			–0.4539*** (0.1473)			–0.4425*** (0.1505)		
Prob > χ^2	**0.6476**			**0.5945**			**0.8241**			**0.7850**		
ρ	–.4713			–.5073			–.2566			–.3016		

*Robust std. errors in parentheses; *** (0.01), ** (0.05), * (0.10); ME = marginal effect.*

Table 4
Job Security

	Basic equation		**… & time preference**		**… & interaction terms**		**… & time preference, interaction terms**	
	MLE model 1		MLE model 2		MLE model 3		MLE model 4	
	Coef.	ME	Coef.	ME	Coef.	ME	Coef.	ME
Outcome equation: job security								
Vocational training								
Apprenticeship	0.0353 (0.1984)	0.0101 (0.0561)	0.0330 (0.1946)	0.0095 (0.0555)	0.0211 (0.2056)	0.0060 (0.0586)	0.0218 (0.2054)	0.0063 (0.0592)
Full-time vocational school	0.1083 (0.2349)	0.0321 (0.0715)	0.1223 (0.2323)	0.0366 (0.0717)	0.0931 (0.2451)	0.0275 (0.0741)	0.1176 (0.2443)	0.0354 (0.0756)
Master craftsman	0.2881 (0.2571)	0.0909 (0.0875)	0.3071 (0.2575)	0.0980 (0.0887)	0.1518 (0.2673)	0.0460 (0.0846)	0.1672 (0.2672)	0.0515 (0.0858)
University of applied sciences	0.2548 (0.3601)	0.0799 (0.1217)	0.2619 (0.3554)	0.0828 (0.1210)	0.0777 (0.3823)	0.0230 (0.1162)	0.0750 (0.3761)	0.0224 (0.1152)
University	0.0129 (0.3612)	0.0037 (0.1047)	0.0389 (0.3635)	0.0114 (0.1081)	–0.0355 (0.3597)	–0.0101 (0.1009)	–0.0030 (0.3675)	–0.0009 (0.1068)
Professional status								
White-collar worker	–0.1842 (0.1875)	–0.0533 (0.0550)	–0.1922 (0.1884)	–0.0561 (0.0556)	–0.2119 (0.1940)	–0.0616 (0.0574)	–0.2201 (0.1958)	–0.0647 (0.0587)
Self-employed person	0.0335 (0.3035)	0.0097 (0.0892)	0.0669 (0.3151)	0.0198 (0.0955)	–0.0095 (0.3213)	–0.0027 (0.0918)	0.0419 (0.3376)	0.0124 (0.1013)
Employment characteristics								
Full-time employee	–0.1796 (0.2115)	–0.0533 (0.0644)	–0.1568 (0.2129)	–0.0466 (0.0648)	–0.1366 (0.2270)	–0.0403 (0.0684)	–0.1032 (0.2301)	–0.0306 (0.0693)
Change	0.0511 (0.1394)	0.0147 (0.0400)	0.0327 (0.1419)	0.0095 (0.0410)	0.1051 (0.1457)	0.0302 (0.0416)	0.0849 (0.1491)	0.0247 (0.0432)
Meeting the needs	–0.0547 (0.2063)	–0.0160 (0.0613)	–0.0567 (0.2070)	–0.0167 (0.0619)	–0.0645 (0.2137)	–0.0189 (0.0639)	–0.0638 (0.2153)	–0.0189 (0.0650)
Computer private	0.1816 (0.1638)	0.0504 (0.0438)	0.1508 (0.1664)	0.0424 (0.0454)	0.2087 (0.1788)	0.0578 (0.0471)	0.1727 (0.1835)	0.0488 (0.0495)
Computer at work	0.5136*** (0.1712)	0.1382*** (0.0422)	0.5174*** (0.1763)	0.1403*** (0.0434)	0.4949*** (0.1854)	0.1338*** (0.0445)	0.4931** (0.1920)	0.1350*** (0.0460)
Number of employees	0.0000** (0.0000)	0.0000** (0.0000)	0.0000** (0.0000)	0.0000** (0.0000)	0.0000** (0.0000)	0.0000** (0.0000)	0.0000** (0.0000)	0.0000** (0.0000)
Individual characteristics								
Age	–0.0730 (0.0573)	–0.0210 (0.0166)	–0.0788 (0.0594)	–0.0228 (0.0175)	–0.1187* (0.0646)	–0.0342* (0.0190)	–0.1298** (0.0659)	–0.0378* (0.0198)
Age squared	0.0009 (0.0007)	0.0003 (0.0002)	0.0010 (0.0007)	0.0003 (0.0002)	0.0014* (0.0008)	0.0004* (0.0002)	0.0015* (0.0008)	0.0004* (0.0002)
Sex	0.4055** (0.1907)	0.1160** (0.0543)	0.3773* (0.1950)	0.1088* (0.0563)	0.6712*** (0.2403)	0.1914*** (0.0690)	0.6456*** (0.2461)	0.1863** (0.0727)
Kids	0.0640 (0.1574)	0.0184 (0.0452)	0.0824 (0.1592)	0.0238 (0.0460)	1.3130*** (0.4860)	0.3646*** (0.1308)	1.4028*** (0.4769)	0.3918*** (0.1304)
Net income	–0.0001 (0.0001)	0.0000 (0.0000)	–0.0001 (0.0001)	0.0000 (0.0000)	–0.0001 (0.0001)	0.0000 (0.0000)	–0.0001 (0.0001)	0.0000 (0.0000)
Married					1.0865*** (0.3898)	0.2178*** (0.0514)	1.1331*** (0.4200)	0.2270*** (0.0532)
Single mother/father					0.1196 (0.4807)	0.0358 (0.1487)	0.1005 (0.4912)	0.0302 (0.1516)
Male & kids					–0.4412 (0.2912)	–0.1155* (0.0698)	–0.4596 (0.2979)	–0.1214* (0.0731)
Married & kids					–1.1481** (0.4801)	–0.3090** (0.1221)	–1.2057** (0.4656)	–0.3268*** (0.1202)
Time preference								
Present-oriented			0.1537 (0.1439)	0.0453 (0.0435)			0.2114 (0.1564)	0.0630 (0.0489)
Constant	0.0774 (1.2193)		0.1218 (1.2658)		0.1312 (1.3269)		0.2083 (1.3555)	
Prob > χ^2	**0.0524**		**0.0799**		**0.0582**		**0.0724**	
N	519		519		519		519	
Participation equation: participation in continuing vocational training								
Influence on participation decision								
Strain	–0.4521*** (0.1214)		–0.4604*** (0.1192)		–0.4774*** (0.1230)		–0.4803*** (0.1237)	
Prob > χ^2	**0.0345**		**0.0589**		**0.0493**		**0.0923**	
ρ	.8448		.8168		.7155		.6766	

*Robust std. errors in parentheses; *** (0.01), ** (0.05), * (0.10); ME = marginal effect; none of the eight workers with a liberal profession could increase his/her job security considerably, which is why they are excluded.*

Table 5

Prospects on the labor market

	Basic equation			… & time preference			… & interaction terms			… & time preference, interaction terms		
	MLE model 1	Probit model 2		MLE model 3	Probit model 4		MLE model 5	Probit model 6		MLE model 7	Probit model 8	
		Coef.	ME		Coef.	ME		Coef.	ME		Coef.	ME
Outcome equation: prospects on the labor market												
Vocational training												
Apprenticeship	0.0351 (0.2067)	–0.0491 (0.2112)	–0.0196 (0.0842)	0.0298 (0.2052)	–0.0492 (0.2110)	–0.0196 (0.0842)	0.0244 (0.2341)	–0.0495 (0.2099)	–0.0197 (0.0837)	0.0237 (0.2188)	–0.0497 (0.2097)	–0.0198 (0.0836)
Full-time vocational school	0.1715 (0.2396)	0.1989 (0.2561)	0.0792 (0.1014)	0.1700 (0.2407)	0.1983 (0.2558)	0.0789 (0.1013)	0.1596 (0.2491)	0.1849 (0.2573)	0.0737 (0.1020)	0.1585 (0.2473)	0.1845 (0.2570)	0.0735 (0.1019)
Master craftsman	–0.1482 (0.3064)	–0.3213 (0.2771)	–0.1256 (0.1047)	–0.1685 (0.2954)	–0.3236 (0.2774)	–0.1264 (0.1047)	–0.2328 (0.3844)	–0.3716 (0.2816)	–0.1443 (0.1046)	–0.2414 (0.3353)	–0.3728 (0.2822)	–0.1448 (0.1048)
University of applied sciences	0.7222** (0.3601)	0.6020 (0.3784)	0.2306* (0.1321)	0.7311** (0.3624)	0.6028 (0.3785)	0.2309* (0.1321)	0.7188* (0.4255)	0.5894 (0.3950)	0.2264 (0.1389)	0.7302* (0.4110)	0.5900 (0.3953)	0.2266 (0.1390)
University	0.4527 (0.3225)	0.4013 (0.3389)	0.1576 (0.1282)	0.4413 (0.3234)	0.3988 (0.3388)	0.1566 (0.1282)	0.4818 (0.3335)	0.4189 (0.3378)	0.1643 (0.1273)	0.4733 (0.3286)	0.4174 (0.3375)	0.1637 (0.1272)
Professional status												
White-collar worker	–0.2540 (0.1839)	–0.2780 (0.1930)	–0.1106 (0.0763)	–0.2537 (0.1846)	–0.2781 (0.1930)	–0.1106 (0.0763)	–0.2976 (0.1914)	–0.3079 (0.1928)	–0.1223 (0.0760)	–0.2957 (0.1892)	–0.3080 (0.1928)	–0.1224 (0.0760)
Self-employed person	–0.3547 (0.3692)	–0.2277 (0.3655)	–0.0897 (0.1414)	–0.3669 (0.3666)	–0.2316 (0.3674)	–0.0913 (0.1420)	–0.4077 (0.3997)	–0.3074 (0.3757)	–0.1202 (0.1422)	–0.4231 (0.3894)	–0.3095 (0.3770)	–0.1210 (0.1426)
Employment characteristics												
Full-time employee	0.3413 (0.2415)	0.4630** (0.2147)	0.1811** (0.0812)	0.3424 (0.2347)	0.4607** (0.2149)	0.1803** (0.0814)	0.3240 (0.3134)	0.4315* (0.2211)	0.1691** (0.0841)	0.3192 (0.2782)	0.4302* (0.2217)	0.1686** (0.0844)
Change	0.1449 (0.1385)	0.0842 (0.1418)	0.0335 (0.0565)	0.1504 (0.1404)	0.0858 (0.1427)	0.0342 (0.0568)	0.1842 (0.1576)	0.1322 (0.1450)	0.0526 (0.0576)	0.1898 (0.1529)	0.1331 (0.1457)	0.0530 (0.0579)
Meeting the needs	–0.3295 (0.2159)	–0.3256 (0.2271)	–0.1289 (0.0882)	–0.3297 (0.2158)	–0.3262 (0.2271)	–0.1291 (0.0882)	–0.3145 (0.2237)	–0.3090 (0.2295)	–0.1225 (0.0895)	–0.3141 (0.2220)	–0.3092 (0.2295)	–0.1225 (0.0895)
Computer private	0.0080 (0.2495)	–0.2038 (0.1811)	–0.0811 (0.0718)	0.0015 (0.2366)	–0.2020 (0.1819)	–0.0804 (0.0721)	0.0168 (0.3315)	–0.1411 (0.1830)	–0.0562 (0.0728)	0.0194 (0.2769)	–0.1401 (0.1839)	–0.0558 (0.0732)
Computer at work	0.4603** (0.2008)	0.2733 (0.1750)	0.1081 (0.0683)	0.4463** (0.1933)	0.2729 (0.1748)	0.1079 (0.0682)	0.4306 (0.2787)	0.2793 (0.1740)	0.1104 (0.0678)	0.4243* (0.2314)	0.2791 (0.1739)	0.1103 (0.0678)
Number of employees	0.0000** (0.0000)	0.0000* (0.0000)	0.0000* (0.0000)	0.0000* (0.0000)	0.0000* (0.0000)	0.0000* (0.0000)	0.0000** (0.0000)	0.0000* (0.0000)	0.0000* (0.0000)	0.0000** (0.0000)	0.0000* (0.0000)	0.0000* (0.0000)
Individual characteristics												
Age	0.0274 (0.0542)	0.0163 (0.0564)	0.0065 (0.0225)	0.0273 (0.0544)	0.0167 (0.0565)	0.0066 (0.0225)	–0.0130 (0.0577)	–0.0178 (0.0585)	–0.0071 (0.0233)	–0.0132 (0.0574)	–0.0176 (0.0585)	–0.0070 (0.0233)
Age squared	–0.0004 (0.0007)	–0.0003 (0.0007)	–0.0001 (0.0003)	–0.0004 (0.0007)	–0.0003 (0.0007)	–0.0001 (0.0003)	0.0000 (0.0007)	0.0000 (0.0007)	0.0000 (0.0003)	0.0000 (0.0007)	0.0000 (0.0007)	0.0000 (0.0003)
Sex	–0.0639 (0.2064)	–0.1471 (0.1994)	–0.0586 (0.0793)	–0.0618 (0.2064)	–0.1449 (0.1999)	–0.0577 (0.0795)	–0.0999 (0.2458)	–0.1441 (0.2351)	–0.0574 (0.0935)	–0.0980 (0.2399)	–0.1433 (0.2359)	–0.0571 (0.0938)
Kids	–0.1064 (0.1568)	–0.1025 (0.1659)	–0.0408 (0.0660)	–0.1104 (0.1577)	–0.1041 (0.1665)	–0.0415 (0.0663)	0.5841 (0.4935)	0.6447 (0.4798)	0.2525 (0.1814)	0.5681 (0.4850)	0.6424 (0.4812)	0.2516 (0.1820)
Net income	–0.0001 (0.0001)	–0.0001 (0.0001)	0.0000 (0.0000)	–0.0001 (0.0001)	–0.0001 (0.0001)	0.0000 (0.0000)	–0.0001 (0.0001)	–0.0001 (0.0001)	0.0000 (0.0000)	–0.0001 (0.0001)	–0.0001 (0.0001)	0.0000 (0.0000)
Married							0.9240*** (0.3341)	0.8517** (0.3567)	0.3108*** (0.1104)	0.9274*** (0.3346)	0.8513** (0.3568)	0.3107*** (0.1104)
Single mother/ father							0.4310 (0.5027)	0.2760 (0.4860)	0.1095 (0.1902)	0.4396 (0.4892)	0.2765 (0.4862)	0.1097 (0.1902)
Male & kids							0.2168 (0.3057)	0.1500 (0.2911)	0.0598 (0.1159)	0.2207 (0.2963)	0.1508 (0.2908)	0.0601 (0.1157)
Married & kids							–0.9948** (0.4770)	–0.9992** (0.4844)	–0.3809** (0.1691)	–0.9819** (0.4732)	–0.9981** (0.4850)	–0.3805** (0.1693)
Time preference												
Present-oriented				–0.0890 (0.1496)	–0.0181 (0.1517)	–0.0072 (0.0604)			0.0000 (0.0000)	–0.0684 (0.1628)	–0.0100 (0.1536)	–0.0040 (0.0612)
Constant	–1.2189 (1.3568)	–0.1794 (1.1884)		–1.1379 (1.3160)	–0.1761 (1.1878)		–0.8605 (1.6400)	–0.1098 (1.1974)		–0.8231 (1.4291)	–0.1073 (1.1977)	
Prob > χ^2	**0.0713**	**0.1515**		**0.1085**	**0.1884**		**0.0202**	**0.0746**		**0.0278**	**0.0945**	
N	527	363		527	363		527	363		527	363	
Participation equation: participation in continuing vocational training												
Influence on part. decision												
Strain	–0.4044*** (0.1402)			–0.4025*** (0.1325)			–0.4351** (0.1692)			–0.4288*** (0.1497)		
Prob > χ^2	**0.3654**			**0.3096**			**0.6316**			**0.5241**		
ρ	.6754			.6450			.5427			.5426		

*Robust std. errors in parentheses; *** (0.01), ** (0.05), * (0.10); ME = marginal effect.*

Table 6

Participation decision

	Basic equation		… & time preference		… & interaction terms		… & time preference, interaction terms	
	Probit model 1		Probit model 2		Probit model 3		Probit model 4	
	Coef.	ME	Coef.	ME	Coef.	ME	Coef.	ME
Vocational training								
Apprenticeship	0.3430* (0.1880)	0.1188* (0.0671)	0.3463* (0.1888)	0.1198* (0.0674)	0.3723** (0.1889)	0.1290* (0.0678)	0.3779** (0.1899)	0.1308* (0.0681)
Full-time vocational school	0.0164 (0.2271)	0.0054 (0.0748)	0.0089 (0.2269)	0.0030 (0.0749)	–0.0170 (0.2325)	–0.0056 (0.0775)	–0.0228 (0.2330)	–0.0076 (0.0778)
Master craftsman	0.7034** (0.3509)	0.1829*** (0.0646)	0.6530* (0.3510)	0.1730** (0.0681)	0.6721* (0.3660)	0.1763** (0.0691)	0.6261* (0.3665)	0.1670** (0.0725)
University of applied sciences	0.7351* (0.4238)	0.1866** (0.0736)	0.8126* (0.4194)	0.1991*** (0.0663)	0.8566** (0.4199)	0.2054*** (0.0628)	0.9437** (0.4149)	0.2172*** (0.0556)
University	0.4547 (0.3801)	0.1299 (0.0897)	0.4302 (0.3783)	0.1238 (0.0912)	0.5547 (0.3835)	0.1519* (0.0818)	0.5315 (0.3838)	0.1466* (0.0836)
Professional status								
White-collar worker	0.0219 (0.1720)	0.0073 (0.0572)	0.0298 (0.1739)	0.0099 (0.0578)	–0.0127 (0.1758)	–0.0042 (0.0581)	–0.0051 (0.1773)	–0.0017 (0.0586)
Self-employed person	–0.3484 (0.3103)	–0.1248 (0.1179)	–0.4091 (0.3138)	–0.1479 (0.1208)	–0.4324 (0.3006)	–0.1566 (0.1160)	–0.4925 (0.3057)	–0.1798 (0.1191)
Employment characteristics								
Full-time employee	–0.2581 (0.1892)	–0.0823 (0.0577)	–0.2879 (0.1894)	–0.0913 (0.0571)	–0.3317* (0.1939)	–0.1042* (0.0574)	–0.3658* (0.1949)	–0.1140** (0.0568)
Change	0.2387* (0.1271)	0.0791* (0.0420)	0.2650** (0.1285)	0.0877** (0.0423)	0.2687** (0.1290)	0.0888** (0.0425)	0.2960** (0.1302)	0.0976** (0.0427)
Meeting the needs	–0.2111 (0.1815)	–0.0665 (0.0541)	–0.2021 (0.1823)	–0.0637 (0.0545)	–0.1975 (0.1834)	–0.0622 (0.0549)	–0.1917 (0.1841)	–0.0604 (0.0552)
Computer private	0.5091*** (0.1464)	0.1783*** (0.0534)	0.5226*** (0.1473)	0.1830*** (0.0537)	0.5274*** (0.1461)	0.1845*** (0.0532)	0.5409*** (0.1472)	0.1892*** (0.0536)
Computer at work	0.6318*** (0.1460)	0.2180*** (0.0516)	0.6146*** (0.1469)	0.2118*** (0.0519)	0.6399*** (0.1464)	0.2204*** (0.0516)	0.6214*** (0.1475)	0.2136*** (0.0520)
Number of employees	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
Individual characteristics								
Age	0.0274 (0.0506)	0.0091 (0.0168)	0.0257 (0.0508)	0.0085 (0.0168)	0.0018 (0.0527)	0.0006 (0.0174)	–0.0010 (0.0527)	–0.0003 (0.0174)
Age squared	–0.0001 (0.0006)	0.0000 (0.0002)	–0.0001 (0.0006)	0.0000 (0.0002)	0.0001 (0.0006)	0.0000 (0.0002)	0.0001 (0.0006)	0.0000 (0.0002)
Sex	0.1720 (0.1772)	0.0571 (0.0588)	0.1964 (0.1775)	0.0651 (0.0588)	0.1634 (0.2074)	0.0541 (0.0685)	0.1797 (0.2083)	0.0594 (0.0687)
Kids	–0.0763 (0.1500)	–0.0253 (0.0497)	–0.0886 (0.1510)	–0.0293 (0.0500)	0.0748 (0.4211)	0.0247 (0.1394)	–0.0177 (0.4260)	–0.0059 (0.1407)
Net income	0.0002* (0.0001)	0.0001* (0.0000)	0.0002* (0.0001)	0.0001** (0.0000)	0.0002* (0.0001)	0.0001* (0.0000)	0.0002* (0.0001)	0.0001* (0.0000)
Married					0.6351** (0.2821)	0.2315** (0.1086)	0.6438** (0.2826)	0.2347** (0.1088)
Single mother/father					0.7233* (0.3800)	0.1892*** (0.0728)	0.7856** (0.3858)	0.2003*** (0.0692)
Male & kids					0.2143 (0.2654)	0.0685 (0.0817)	0.2296 (0.2660)	0.0731 (0.0814)
Married & kids					–0.4184 (0.4211)	–0.1396 (0.1407)	–0.3426 (0.4262)	–0.1141 (0.1424)
Time preference								
Present-oriented			–0.2718** (0.1283)	–0.0920** (0.0441)			–0.2796** (0.1293)	–0.0945** (0.0444)
Influence on part. decision								
Strain	–0.4329*** (0.1261)	–0.1466*** (0.0434)	–0.4254*** (0.1264)	–0.1439*** (0.0434)	–0.4630*** (0.1280)	–0.1565*** (0.0440)	–0.4542*** (0.1285)	–0.1533*** (0.0440)
Constant	–1.4183 (1.0396)		–1.2642 (1.0450)		–1.1700 (1.0461)		–0.9853 (1.0501)	
Prob > χ^2	**0.0000**		**0.0000**		**0.0000**		**0.0000**	
N	527		527		527		527	

*Robust std. errors in parentheses; *** (0.01), ** (0.05), * (0.10); ME = marginal effect.*